SYNOPSIS

Ph.D in Computer Science

OPTIMIZED HYBRID FORECASTING MODEL USING ENHANCED DEEP LEARNING BASED APPROACH FOR TRANSACTION MANAGEMENT IN COMMODITY TRADING

By

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1. INTRODUCTION

Forecasting commodity price movements are critical for economics and trade decisions for industries that rely on raw materials, agricultural goods and natural resources. Commodities include oil and gas to agricultural produce, metals, and minerals. In trade market, commodity price forecasting and trend analysis are critical for making informed decisions thereby reducing risks and maximizing resource allocation. Forecasting commodity prices on the other hand is a difficult endeavour riddled with challenges like market volatility, data quality and availability, short and long-term forecasts, environmental issues and few external factors that includes government rules, trade agreements and currency exchange rates. Derivatives are financial products [1] that are traded on exchanges, whose values are obtained from underlying assets such as stocks, commodities, bonds, farm animals, interest rates, currencies, exchange rates and indices. Transaction management in trading commodity derivatives operates based on trading strategies and traded volumes, considering price per lot size. The key success factor for effective transaction management relies on high returns within specific turnaround timelines.

In commodity trading market, transaction management approaches are devised and strategized by the trader based on volume and lot size of the purchase or sale for each commodity investment based on price. Research studies and observations indicate the benefit of applying analytical approach to gain deeper market insights, which the traders can capitalize to make profits. Considering the complexity and dimensionality of data, current economic situations in commodity market, trends and variations, use of deep learning approaches to build forecasting model are recommended with time series decomposition.

With a wide range of fluctuations due to market dynamics, trader finds it as a challenge to understand price movements and make trade decisions. The commodities market is characterized by significant uncertainty [2], needing rigorous research to understand and interpret trade patterns. The prime objective of this research work is to build an analytical model to forecast commodity trade price with enhanced performance capability, which can handle outliers and anomalies, thereby provide trade directions based on forecast to commodity traders using deep learning based approaches - Long Short Term Memory (LSTM) and prophet model for time series decomposition.

Forecasting based on time series has gathered momentum as decision making is supported based on data based derivatives. Time series refers to collection of statistical data in chronological order. Time Series analysis refers to a mechanism of predicting the data for the future providing insights, based on historical data.

Novelty of this approach revolves around the mechanics used to handle outliers and improvise signal strength, which enhances the robustness of the model. The impact of anomalies are thereby minimized which results in boosting the performance capability of the model. Learning derivative of this approach indicates that calculative trade-off can be decided by traders based on forecasted data. When decision making is backed based on the data insights, quality plays a major focus in decision making for the trader in response to market dynamics will yield long term benefits.

With non-linear factors that impact trade, proposed research approach aims to forecast price movements and create future timeframes with seasonality after evading anomalies. Evading the outliers and white noise along with focus on seasonality brings ease of focus on the business implementation. The choice to apply multiple kernels configurations in Long Short Term Memory model brings weight optimization and dropout regularization helps to reduce the impact of overfitting. Dropout works by effectively dropping a neuron from the input or hidden layers [3]. Optimization using dropout involves applying dropout layers in LSTM and also within recurrent connections to regularize the model. This process reduces overfitting, improves generalization and enhances the robustness and performance of deep learning models, particularly in time series forecasting.

Further enhancement of the model with deep learning Prophet Model integrated with a layer of anomaly detection has resulted in valuable outcomes to identify trends, pattern and seasonality. In comparison to traditional neural network and LSTM methods, it is observed that hybrid approach using enhanced multi-kernel LSTM with Neural Prophet and regressors brings optimization in forecasting model thereby reduce the impact of outlier challenges with enhanced performance efficiency.

The context of the current study aims to enhance commodity trading benefits by raising the degree of effectiveness in transaction management strategies. The outcome of this study is derived based on commodity trading dataset to build an analytical model to forecast trade price.

2. LITERATURE SURVEY

Bilin Shao et al. [4] developed a novel method for forecasting the price of nickel metal. The approach was based on the Particle Swarm Optimization Algorithm (PSO), an optimization technique inspired by the collective behavior of particles in nature. The modifications to the classic PSO algorithm makes this method distinctive. It introduces two major changes: a nonlinear decreasing assignment mechanism and the integration of a sine function. These changes were intended to improve PSO's performance. The nonlinear decreasing assignment approach improves the manner in which the inertia weight, a critical parameter in PSO, was updated during optimization. Simultaneously, the sine function maximizes the learning factor which is another important component in the PSO process. The study recognizes the need for future research to prove the model's success in short-term forecasting, which was a vital step in assuring the resilience and practicability of the approach in the dynamic world of commodity price prediction. However, more validation of the model's performance was required in this study, particularly in the context of short-term price predictions.

Meysam Naderi et al. [5] introduced four forecasting methods—Least Squares Support Vector Machine (LSSVM), Genetic Programming (GP), Artificial Neural Network (ANN), and Auto-Regressive Integrated Moving Average (ARIMA) to predict monthly oil price (MOP), daily gas price (DGP) and annual interest rate (AIR). The Bat Algorithm (BA) was employed to optimally combine these methods. Historical data from the Central Bank of Iran was used to validate the model. Performance was assessed using R^2, AAREP, RMSE and cumulative probability distribution versus absolute relative error percentage. The BA-optimized method outperformed others, showing the highest R^2 and lowest RMSE, with RMSE reductions compared to the other methods. Further study recommends to apply multiple econometric factors using machine learning algorithms.

N.Deepika and M. Nirupama Bhat [6] described use of an efficient prediction method based on Kalman Filter using Accelerated Gradient Long-Short Term Memory (AG-LSTM) for stock market price prediction. The method's output was analysed with and without a Kalman filter, showing that the Kalman filter technique enhanced stock market prediction performance. For Microsoft stock data, the proposed AG-LSTM model with the Kalman filter achieved high level of accuracy compared to the existing AG-LSTM model. Furthermore, improvements to accuracy can be achieved considering other correlation weighting features.

Wong Pee Shoong et al. [7] presented an improved LSTM technique using Three-Point Moving Gradient for Stock Price Forecasting. The Long Short-Term Memory (LSTM) technique, while effective at recognizing patterns, does not emphasize the significant relationship between past and future values in a time series. This research proposes an alternative LSTM method that considers past, current, and subsequent prices by predicting the Three-Point Moving Gradient (TPMG) of stock market prices. Using reversed Linear Regression (LR) and the mean price, this method can accurately forecast prices. The results show that this approach is as precise as the conventional LSTM. Overall, using TPMG in LSTM provides better predictions, with TPMG graphs being closer in spread to the original price points compared to standard LSTM. Considering the market undercurrents, identifying econometric impact can result in prediction advancements.

A Novel Anomaly Detection Approach for Nifty Stocks using Machine Learning for Construction of Efficient Portfolio to Reduce Losses and Protect Gains was described by Virrat Devaser and Priyanka Chawla [8]. Authors investigated detecting abnormalities while combining fundamental and technical aspects of stock market data. Multiple machine learning approaches were employed to identify various types of abnormalities, using a bagging strategy that incorporated a Class One Support Vector Machine, a Local Outlier Factor and other techniques. Given that companies' valuations vary across sectors, data was segmented by industry type, such as banking, cement, and energy. The portfolio was constructed based on anomaly scores, which helped remove equities from the portfolio, avoiding losses and preventing profit erosion. Also, addressing the impact of overfitting can reduce the outlier impact and anomalous effects.

Mohammad Javad Bazrkar and Soodeh Hosseini [9] employed supervised learning algorithms and particle swarm optimization algorithm to predict stock prices by preventing over-fitting and bring improvement in forecast accuracy. This paper introduces a machine learning approach called Support Vector Machine (SVM) that uses existing data to predict new stock data. To enhance accuracy and prevent over-fitting, the Particle Swarm Optimization (PSO) algorithm was employed to select the best SVM parameters. The proposed SVM-PSO method was compared with other methods, including SVM, Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM) and use of SVM-PSO algorithm outperformed in terms of accuracy. Additionally, provision to accommodate choice from domain users can bring deeper market insights.

3. PROBLEM DEFINITION

Market dynamics lead to significant price fluctuations, posing a challenge for traders to interpret movements and make informed decisions. Market dynamics introduce substantial price volatility, which complicates traders' efforts to accurately interpret and understand these fluctuations. This volatility challenges traders in predicting future price movements and making well-informed decisions, as the rapid and unpredictable changes can obscure underlying trends and patterns. Commodity markets have experienced various instances of large volatility over the last two decades, with the fundamental driving force being commodity demand and supply [10].

This research aims to develop an advanced analytical model to forecast commodity trade prices with improved performance. The model effectively manages outliers and anomalies, ensuring more accurate predictions. It employs deep learning based approaches such as Long Short-Term Memory (LSTM) for time series decomposition and integrates with the Neural Prophet model. By combining these techniques, the model provides reliable trade directions to commodity traders, helping them make insightful decisions based on accurate forecasts.

4. OBJECTIVES OF THE RESEARCH

The primary objective of the research work is summarized as follows:

- To build an analytical model to forecast commodity trade price with enhanced performance capability, which can handle outliers and anomalies, thereby provide trade directions based on forecast to commodity traders

The secondary objectives of the research work are summarized as follows:

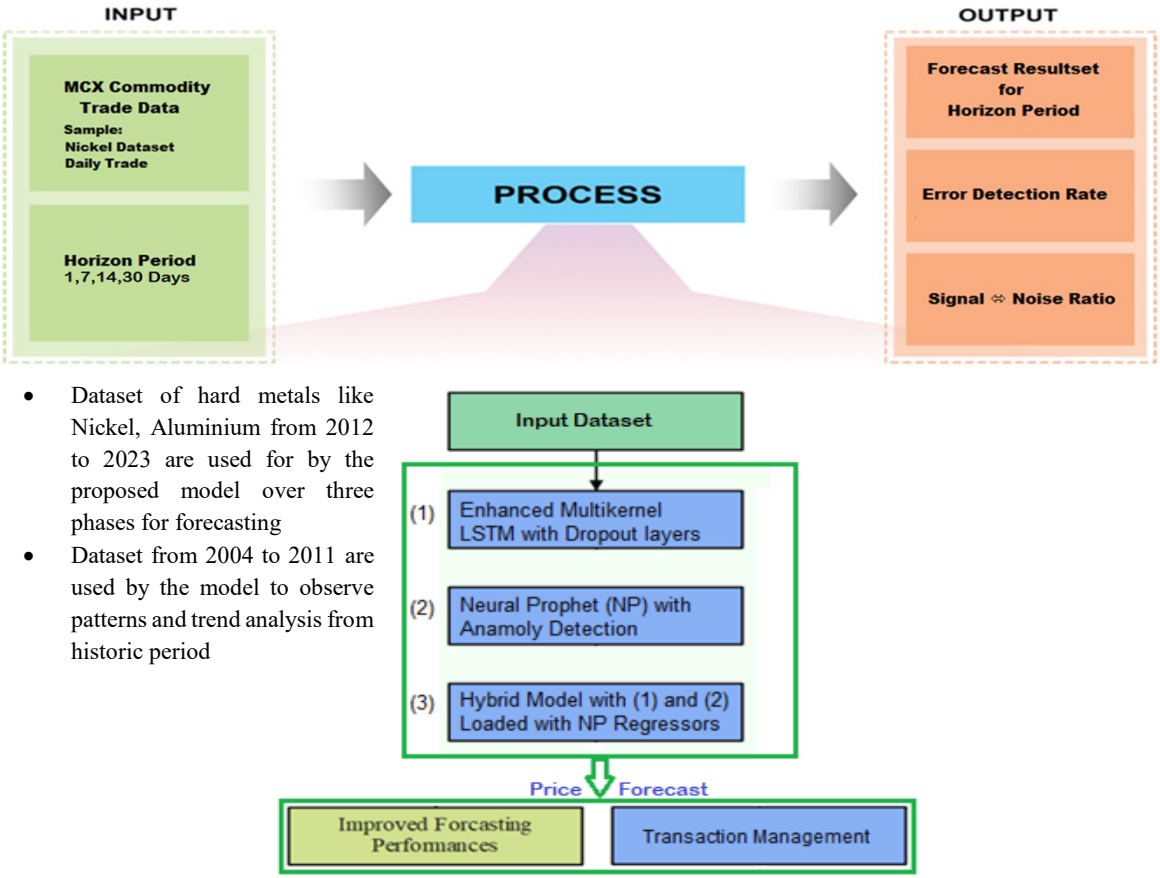
- To handle temporal dependencies, analyze seasonality and trends, thereby bring context awareness to non-stationary data with ability to forecast across flexible time horizons
- Use of dropout regularization enables the model to reduce the impact of randomness and over-reliance on specific nodes, thereby improving the performance capability

With these objectives, the research work aims to bring high level of accuracy by leveraging the benefits of analytics, deep learning algorithms and time series decomposition to make the model capable of capturing complex patterns and non-linear relationships, investigating the most repeatable patterns and trends.

5. RESEARCH METHODOLOGY

The research study aims to develop a model for forecasting commodity trade prices and improving model performance by managing outliers and anomalies. Following steps are performed to apply analytical and algorithmic approaches in building the forecasting model.

1. Pre-processing and Normalization: Dataset is extracted from Multi-Commodity Exchange (MCX, India) in Open-High-Low-Close (OHLC) where daily trade volumes are used as data feed. Dataset of hard metals viz., Nickel, Aluminium are used to observe and compare trends and patterns. Exploratory data analysis techniques are used to analyse and understand key characteristics of data, uncover patterns and identify relationships between variables. This helps to cleanse datasets and create a stable platform with rich data.
2. Pattern Analysis: Use of time series algorithms helps to understand value changes over time, observes trends, repeated patterns and unwrap seasonal behaviour.
3. Performance Enhancement: Anomaly and outlier detection improvise forecasting capabilities, which are validated based on error detection metrics.
4. Forecast-based Profiling: Develop a profile to provide trade directions based on the forecast to assist traders to gain market insights.



- Dataset of hard metals like Nickel, Aluminium from 2012 to 2023 are used for by the proposed model over three phases for forecasting
- Dataset from 2004 to 2011 are used by the model to observe patterns and trend analysis from historic period

FIGURE 1 RESEARCH APPROACH AND METHODOLOGY

5.1. Price Forecasting Model using Enhanced Multi-Kernel LSTM (E-MKLSTM) with dropout regularization evading outliers

The first phase of work aims to develop an efficient forecasting model to predict commodity trade prices, focusing on managing outliers to improve accuracy by reducing noise in time series. The model leverages Long Short Term Memory with multiple-kernel configurations, within each layer to enrich representations and optimizes weights over the lower and upper bounds. Hyper-parameters, such as batch size, number of neurons, dense layer units, dropout rate, weight adaptations, learning rate, and number of epochs, are tuned using the Keras tuner for optimal performance.

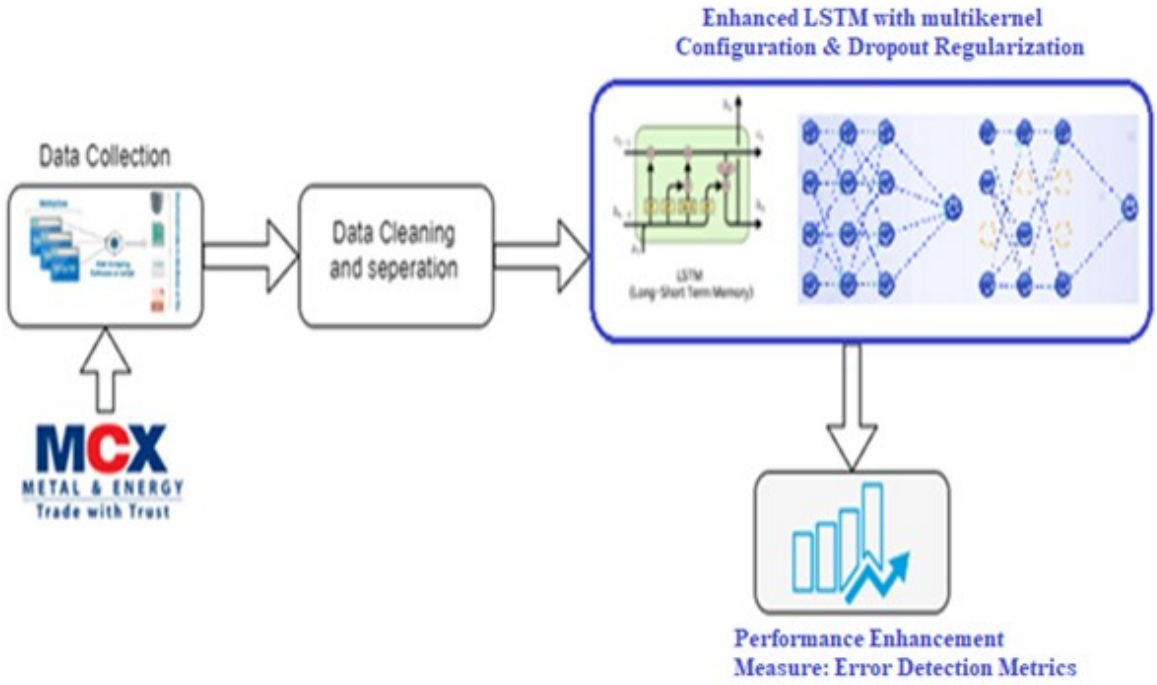


FIGURE 2 ENHANCED MULTI-KERNEL LSTM WITH DROPOUT REGULARIZATION

Dropout regularization is employed to reduce the risk of overfitting by probabilistically decreasing network capacity and regularizing the output. The model also uses dropout to regularize and optimizes weights over the span bound, which are validated using a "Train - Validate - Test" approach with various split ratios 80-20[15, 5] and 70-30[20, 10]. This methodology ensures robust and accurate price forecasting for commodity trading through advanced deep learning techniques and thorough validation processes. Limitations were observed in the model due to short term prediction capabilities. Apart from price, deeper insights in terms of trend and seasonality are required for making trade directions. Also, use of alternative approach for cross validation can make the model learn iteratively through multiple folds. Hence, the next phase of work focuses on enhancement of the price forecast model to overcome these limitations.

5.2. Enhanced Price Forecasting Model using Integrated Neural Prophet (NP) and Anomaly Detection (AD)

In this second phase of research work, aim is to enhance the price forecasting period to wider horizon period ranging from one day to a month along with signal optimization to predict prices for commodity trading. The prediction of a time-series is a challenging task because of the inherent complexity of data, non-linearity of time series information and significant noise. The criteria include detecting anomalies through white noise detection and applying min-max normalization for calculation of threshold limits.

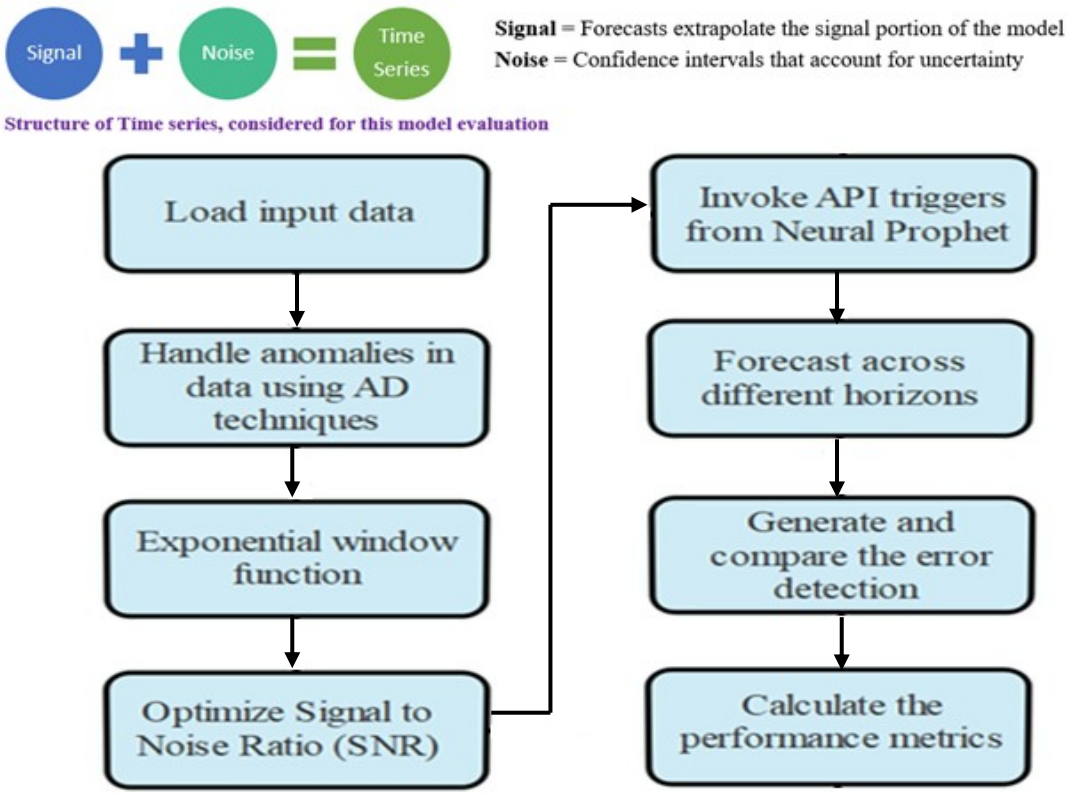

Signal
Noise
Time Series
Signal = Forecasts extrapolate the signal portion of the model
Noise = Confidence intervals that account for uncertainty
Structure of Time series, considered for this model evaluation
Load input data
Handle anomalies in data using AD techniques
Exponential window function
Optimize Signal to Noise Ratio (SNR)
Invoke API triggers from Neural Prophet
Forecast across different horizons
Generate and compare the error detection
Calculate the performance metrics

FIGURE 3 INTEGRATED NEURAL PROPHET WITH ANOMALY DETECTION

The technical choices involve using Neural Prophet, exponential window slicing, and cross-validation (K-Folds) with a "forward chaining" mechanism. The research outcome includes forecasting across the window period, providing market insights based on seasonality, improving error detection performance metrics and increasing optimized signal strengths. The model reveals seasonality and trend based on the time period forecast. Additionally, incorporating holiday periods for specific regions can offer deeper market insights. However, observations indicate that iterative cycles are necessary to handle temporal patterns when dealing with large and complex datasets. These challenges can be overcome with the proposed hybrid approach elaborated in the next phase of the work.

5.3. Hybrid Model using E-MKLSTM and Neural Prophet with Regressors for Price Forecasting

In this phase of research work, the objective is to build a highly accurate model for forecasting commodity prices using an integrated approach combining E-MKLSTM and Neural Prophet with regressors and to minimize residual errors. The aim is to achieve this by incorporating outlier detection, regressor analysis, min–max normalization and Generative Additive Model (GAM) to implement holiday components. This approach provisions implementation of country-specific holidays for required region that ensures accurate matching between response and predictor variables using evaluation parameters such as day of the week, week of the year, and events with year.

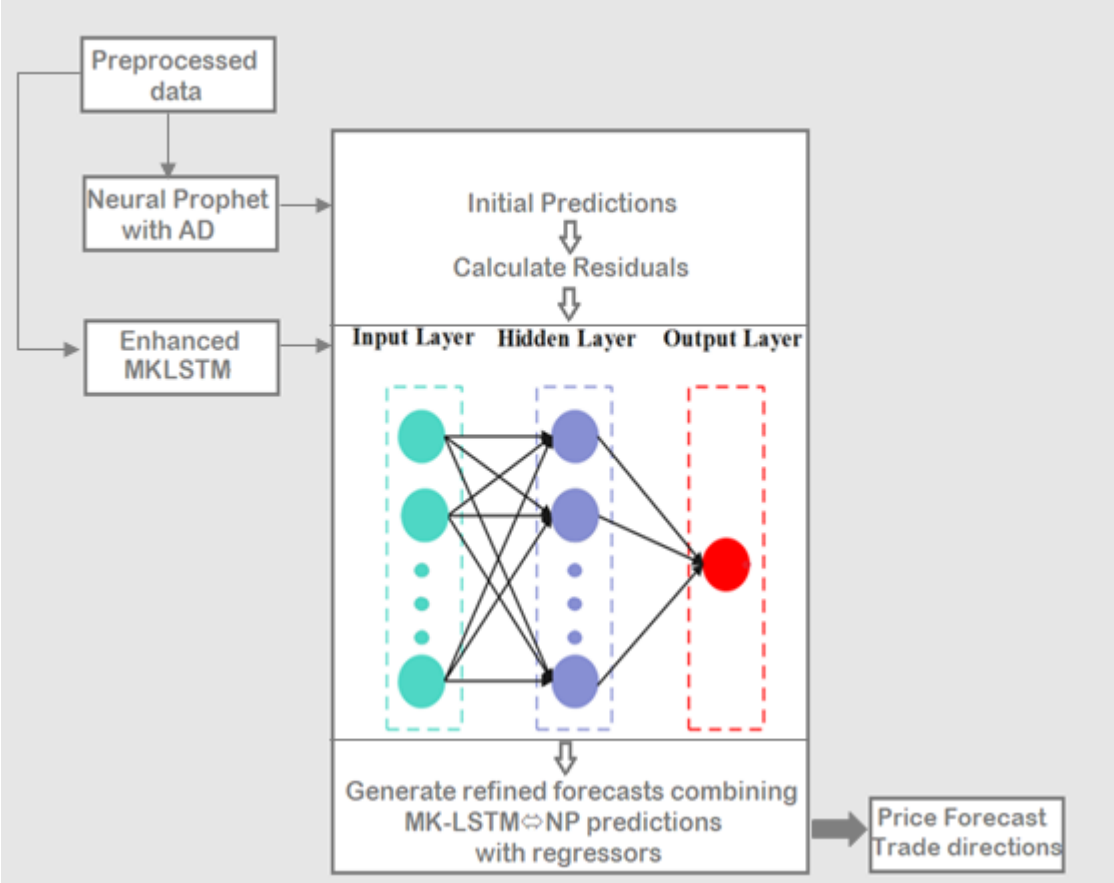


FIGURE 4 HYBRID MODEL WITH USE OF E-MKLSTM AND NEURAL PROPHET

The hybrid E-MKLSTM-NP model captures a wide range of temporal patterns and external influences, making predictions more accurate, robust, and interpretable. It outperforms other methods (as shown in the results) by efficiently handling outliers and minimizing loss functions. This model is seen to produce optimized research outcome, overcoming the challenges mentioned in 5.1 and 5.2.

6. EXPERIMENTAL RESULTS AND DISCUSSIONS

6.1 Error Detection Metrics

Literature study and research outcome about forecasting models indicate that efficiency level can be evaluated based on the rate of error detection metrics. Signal ⇔ Noise ratio can be used to indicate strength of the model. The different indicators of error rates are, Noise to Signal ratio [NSR], measure of Normalized Mean Square Error [NMSE], and Mean Square Error [MSE]. Other statistical measures – Mean, Variance and Standard Deviation are used to validate presence of white noise in the data set. These metrics can be evaluated utilizing the formulae given below:

- MSE, RMSE and MAE - Mean Square Error (MSE) is a metric used to measure the average squared magnitude of the errors between the predicted values and the actual values. RMSE is a metric that measures the square root of the average squared magnitude of the errors between the predicted values and the actual values. It is calculated as the square root of the MSE. Mean Absolute Error (MAE) is a metric used to measure the average magnitude of the errors between the predicted values and the actual values. [Attributes are: n represents sample size, y_t, μ_t represents predicted sequences]

$$MSE = \frac{1}{N_s}\sum_t (y_t - \mu_t)^2 \quad [6A]$$

$$RMSE = \sqrt{MSE} \quad [6B]$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_t - \mu_t| \quad [6C]$$

- NMSE - Normalized Mean Square Error (NMSE) is an estimator of the overall deviations among measured and predicted values. The NMSE is calculated using equation

$$NMSE = \frac{\sum_t (y_t - \mu_t)^2}{\sum_t (y_t - \bar{y})^2} \quad [6D]$$

- NSR – The Noise to Signal ratio (NSR) is expressed in decibels (dB) and relates to both signal power and noise power, and it is calculated using the below equation

$$NSR\ (dB) = 10\ log_{10} \frac{\sum_t (y_t - \mu_t)^2}{\sum_t y_t^2} \quad [6E]$$

- White noise detection in time series forecasting Indicates that the series is random and lacks trend. If μ is 0 and σ remains constant, it indicates that series lacks a predictable pattern. Whereas, if the time series is not a white noise then trend, pattern and seasonality can be identified.

$$\mu = \frac{1}{n} \sum_{t=1}^{n} X_t \quad [6F] \qquad \sigma = \sqrt{\frac{1}{n}\sum_{t=1}^{n} (X_t - \mu)2} \quad [6G]$$

6.2 Phase 1 Results : Price Forecasting Model using Enhanced Multi-Kernel LSTM (E-MKLSTM) with dropout regularization evading outliers

TABLE 1: ERROR DETECTION MEASURES USING MK-LSTM LEARNING MODEL FOR PRICE FORECASTING

Price Forecasting Models	Error Detection Measures [Horizon Period 1 day / No. of cycles: 10]**		
	MSE (Sq. units of Error Rate)	N-MSE (Unit: Error Rate Deviation)	Noise ⇔Signal NSR Ratio (Unit: dB)
LSTM with Moving Averages	2.81	2.05	0.59
Gaussian Process LSTM	2.57	1.92	0.46
MK-LSTM	**2.33**	**1.64**	**0.33**

** 95% of iterations – minimal variance

Outcome: Use of weight optimization helps the model to reduce noise to 0.33db

TABLE 2: ERROR DETECTION MEASURES USING ENHANCED MK-LSTM LEARNING MODEL FOR PRICE FORECASTING

Price Forecasting Models	Error Detection Measures [Horizon Period 1 day / No. of cycles: 10]**		
	MSE (Sq. units of Error Rate)	N-MSE (Unit: Error Rate Deviation)	Noise ⇔Signal NSR Ratio (Unit: dB)
Multi-kernel LSTM	2.33	1.64	0.33
Enhanced MK-LSTM**	**2.26**	**1.48**	**0.27**

**With drop out regularization, 95% of iterations – minimal variance

Outcome: With dropout regularization in this model, noise is reduced to 0.27db

Research work of phase 1 aims to build a price forecasting model using Enhanced Multi-Kernel LSTM (E-MKLSTM) with dropout regularization evading outliers. Outcome from phase 1 of the work is presented above. Table 1 summarizes the outcome of using comparison of LSTM using Moving Averages and Gaussian Process with the proposed Multi-Kernel LSTM (MK-LSTM) model, which indicates weight optimization helps to reduce noise to 0.33 dB. Table 2 indicates the outcome with the inclusion of a "dropout" layer with MK-LSTM making it an enhanced model that mitigates the impact of outliers and randomness, preventing over-reliance on specific nodes. By utilizing a loss function, it reduces overfitting and identifies various temporal patterns. This model employs a "Train-Validate-Test" approach, which simplifies the process and reduces computational cycles. Formulae for deriving the results in Table 1 and 2 are elaborated in Section 6.1.

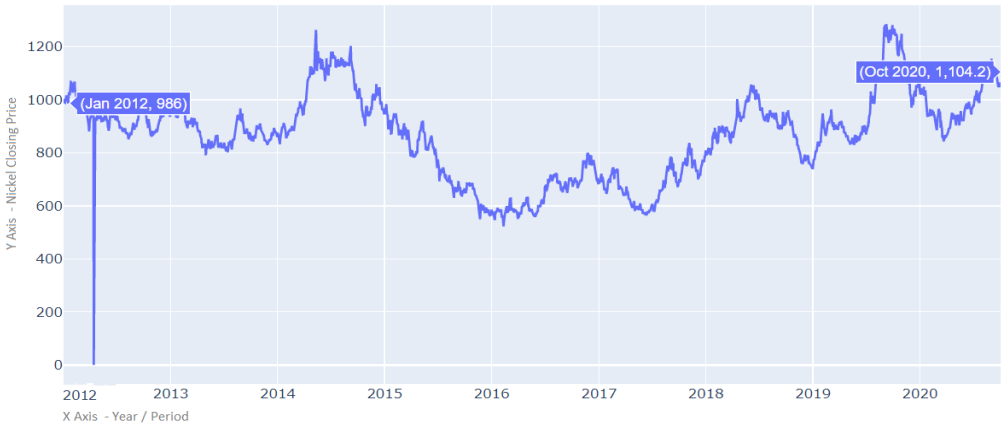


FIGURE 5 TIME SERIES TO INDICATE PRICE MOVEMENT AND FORECAST FOR PERIOD OF 1 DAY

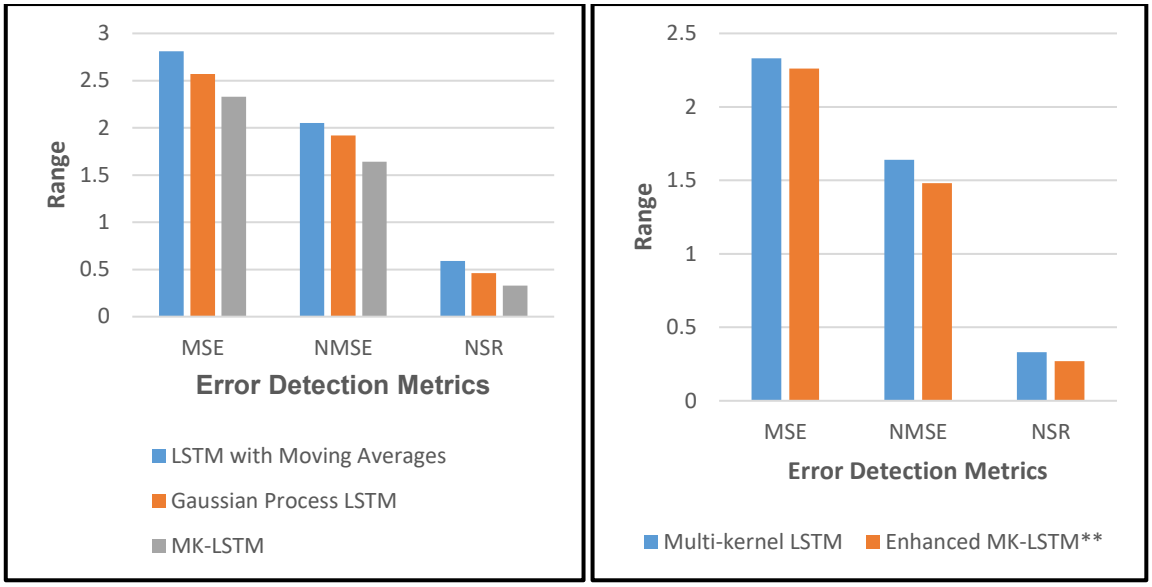


FIGURE 6 GRAPHICAL REPRESENTATION OF ERROR DETECTION MEASURES FOR TABLE 1 AND 2

Figure 5 and 6 depicts the graphical representation of results of forecast and error detection metrics. With enhanced MK-LSTM, error detection measures show performance improvement with noise reduction from 0.33 dB to 0.27 dB.

6.3 Phase 2 Results : Enhanced Price Forecasting Model using Integrated Neural Prophet and Anomaly Detection

TABLE 3: SEASONALITY USING INTEGRATED NEURAL PROPHET MODEL WITH ANOMALY DETECTION

Horizon Period (in days)	Seasonality Configuration using Neural Prophet
07	Daily seasonality factor enabled using Prophet pf=NeuralProphet (daily_seasonality=true)
14	Weekly seasonality factor with Prophet pf=NeuralProphet (weekly_seasonality=true)
30	

Research work of phase 2 focuses on enhancing the capability of the price forecasting model to scale the duration of the forecast built using integrated Neural Prophet (NP) with anomaly detection. Outcome from phase 2 of the work is presented below. Table 3 summarizes the seasonality factor assigned based on the horizon days. White noises are detected using the Autocorrelation Function (ACF). ACF is used to split data set into four slices or chunks to design and create four data frames. Mean and standard deviation are calculated for each data frame in the time series over iterative cycles to identify presence of anomalous trend.

Figure 7 describes the use of Min-Max Normalization to represent data points for observation of anomalous behaviour. Figure 8 represents forecasted value for a specific horizon period of 14 days with indication of upper and lower bound values.

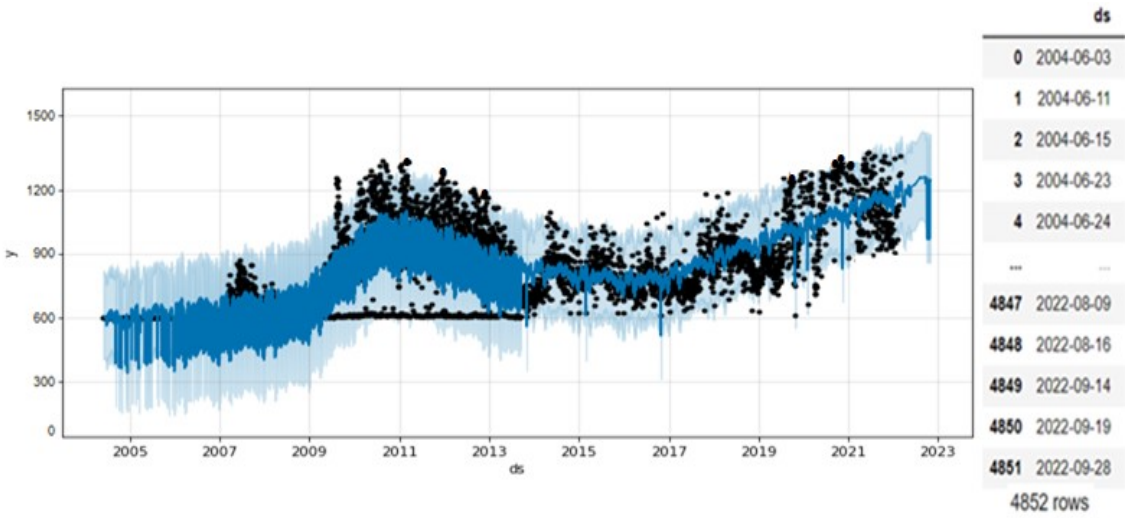


FIGURE 7 MIN-MAX NORMALIZATION WITH DATA PLOTS USING NICKEL DATA SET FROM MCX

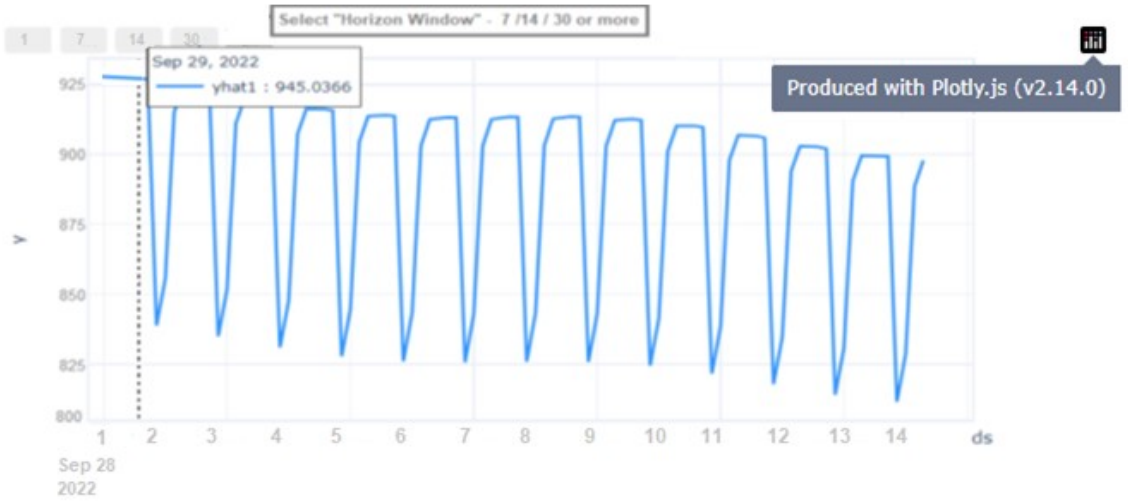


FIGURE 8 FORECAST INDICATING UPPER AND LOWER BOUND FOR HORIZON PERIOD = 14 DAYS

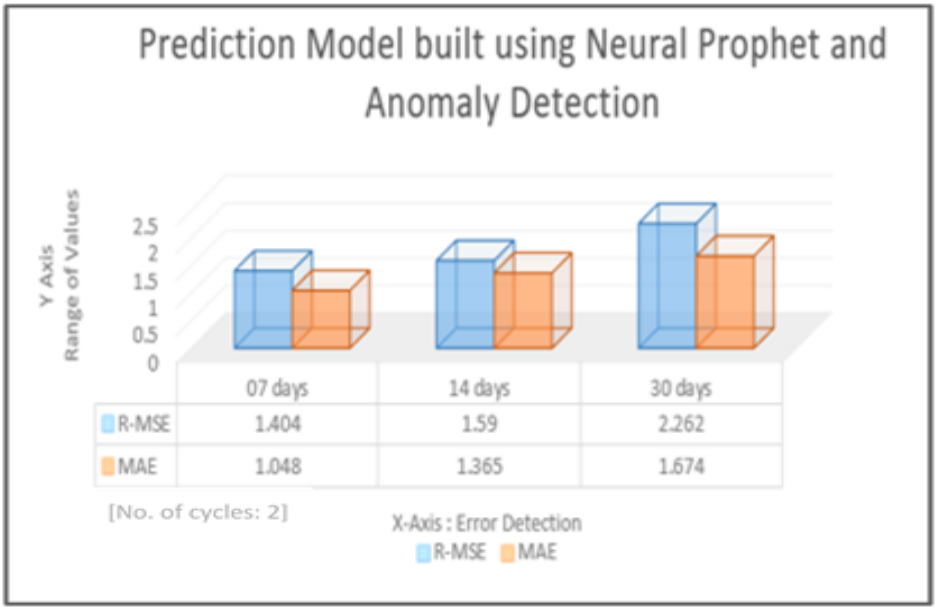


FIGURE 9 ERROR DETECTION METRICS FOR HORIZON PERIOD 7, 14 AND 30 DAYS

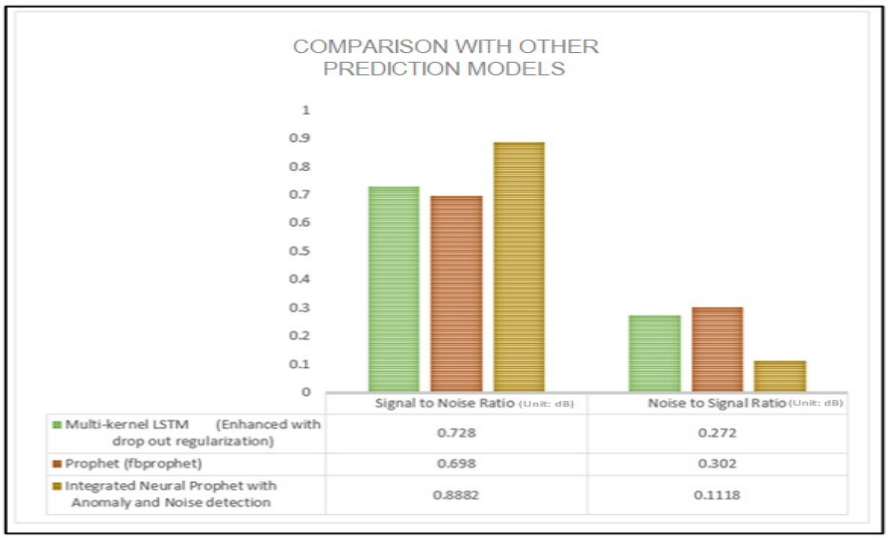


FIGURE 10 COMPARISON OF SIGNAL STRENGTH WITH OTHER PREDICTION MODELS

Outcome: With this integrated model, signal strength indicates 0.89db, leaving noise residual of 0.11 dB for horizon period of 14 days

Figure 9 represents the summarized view of error detection metrics using R-MSE and MAE to represent magnitude of error present. Figure 10 represents the comparison with other prediction models indicating outcome of the proposed approach ranks higher with optimized signal strength of 0.89 dB, leaving noise residual of 0.11 dB for horizon period of 14 days. Formulae for deriving the results in Figure 9 are elaborated in Section 6.1.

6.4 Phase 3 Results : Hybrid Price Forecasting Model using E-MKLSTM and Neural Prophet with Regressors

TABLE 4: RMSE ERROR DETECTION USING HYBRID MODEL WITH E-MKLSTM AND NP WITH REGRESSORS

Data set from MCX: Hard metals Nickel and Aluminium - Horizon period: 14 days [Cycle: 1, 2]

Price Prediction Algorithmic Approaches	RMSE Dataset: Hard Metal – Nickel RMSE & MAE represented in units of error rate deviation	RMSE Dataset: Hard Metal – Aluminium RMSE represented in units of error rate deviation
Fb-Prophet	2.7426	3.0149
NP	2.4290	2.6318
LSTM	2.3089	2.5874
E-MKLSTM ⇔ NP	**1.7797**	**1.9356**

Outcome: The calculated error residual using RMSE indicates ~ 1.7 to 1.9 units deviation for horizon period of 14 days (in two cycles) across various hard metals

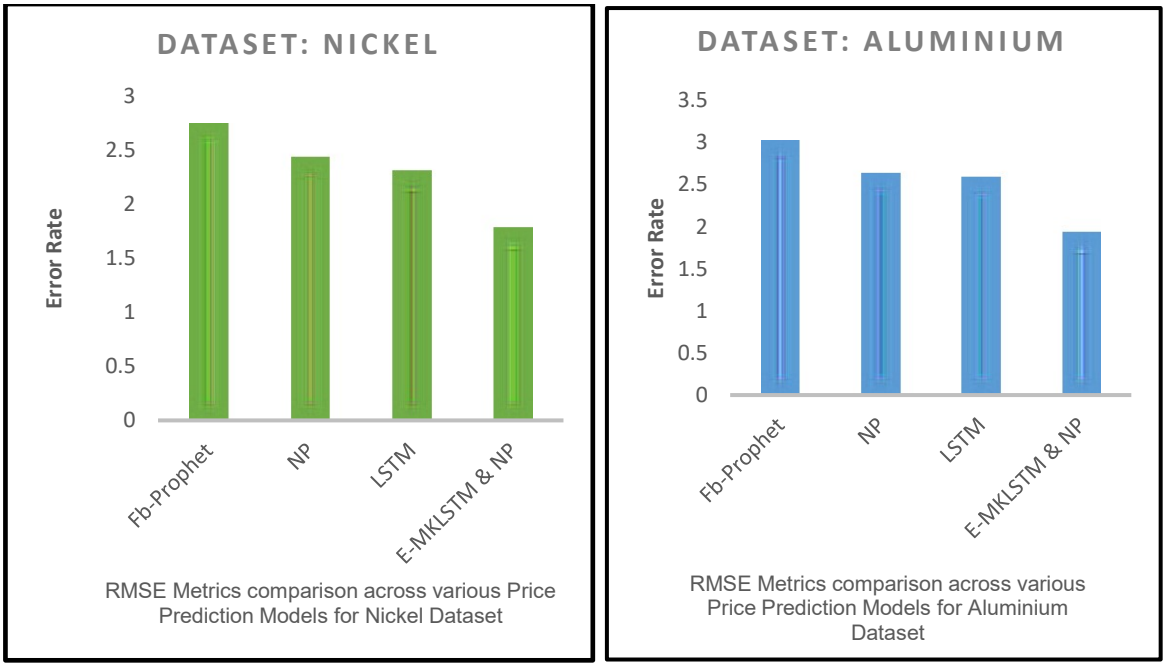


FIGURE 11 RMSE METRIC COMPARISON USING PRICE PREDICTION MODELS FOR RESULTS IN TABLE 4

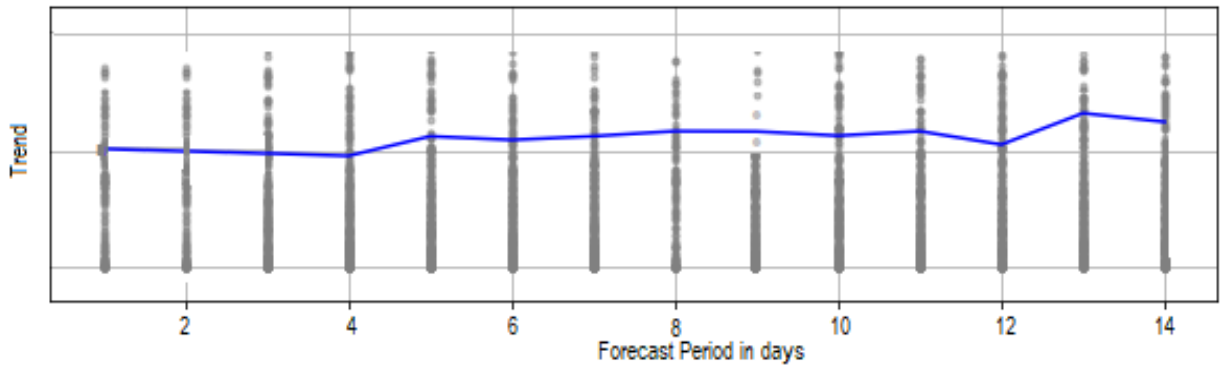


FIGURE 12 FORECAST - TREND ANALYSIS WITH NICKEL DATA SET FOR HORIZON OF 14 DAYS

Research work of phase 3 integrates enhanced Multi-Kernel LSTM and Neural Prophet with regressors into a hybrid approach. Outcome from phase 3 of the work is presented above. Inherent benefits indicated in phase 1 and phase 2 such as regularization, noise removal and signal optimization were continued to be observed during the application of integrated approach to this model. Addiitonally, use of regressors help to capture seasonality's in-depth or special events that may influence the time series. By incorporating relevant features that capture periodic patterns or unusual occurrences, Neural Prophet can better adapt to the nuances present in the data. Neural Prophet's neural network architecture enables it to uncover complicated patterns and relationships between the target variable and the regressors attribute. Table 4 indicates result of RMSE after applying cross validation of the model on datasets of hard metals from MCX viz., Nickel and Aluminium. Validation applied using RMSE for identification of magnitude of errors. Formulae for deriving the results in Table 4 are elaborated in Section 6.1.

FIGURE 13 MAPPING TRADE CRITERIA BASED ON FORECAST TREND USING TENSOR BOARD

Figure 11 uses graphical representation of RMSE based comparison of this hybrid approach with other price forecasting models. It indicates reduction of error residual using this hybrid approach. Figure 12 represents forecast trend analysis of price movement. Figure 13 depicts the trend patterns using TensorBoard for the selected price range, which provides trade directions to trader for chosen horizon period.

The enhanced Multi-Kernel LSTM (E-MKLSTM) component excels in managing long-term dependencies, ensuring the retention of relevant information over extended periods. Additionally, Neural Prophet's strength in modelling seasonality and trends allows for accurate representation of recurring patterns and long-term movements which are critical for precise forecasting.

With this, the hybrid model called the E-MKLSTM⇔NP model captures a wide range of temporal patterns and external influences, making predictions more accurate, robust, and interpretable using regressors. This hybrid model captures complex patterns and non-linear relationships within the data, by efficiently handling outliers and minimizing loss functions. Thus, results indicate the reduction of error using this hybrid model produces optimized research outcome making the model suitable to handle complex data volumes.

7. CONCLUSION

This proposed model brings significant optimization in forecasting commodity prices by effectively addressing outlier challenges and enhancing overall performance efficiency. Leveraging the combined strengths of advanced analytics, deep learning algorithms and time series decomposition, the research achieves remarkable accuracy by reduction in error rate of deviations. The model captures complex patterns and non-linear relationships within the data, which traditional models often overlook. The multi-kernel LSTM (E-MKLSTM) component excels in managing long-term dependencies, ensuring the retention of relevant information over extended periods. Additionally, Neural Prophet's strength in modelling seasonality and trends allows for accurate representation of recurring patterns and long-term movements, which are critical for precise forecasting.

Context awareness is another key feature incorporated with inclusion of regressors, such as country-specific holidays for required region, thereby enhancing the model's ability to account for external factors influencing commodity prices. Use of regressors results in improved forecast accuracy. The model's robustness to non-stationary data components further demonstrates its suitability for real-world applications, where data properties often change over time. It is versatile, capable of handling both short-term and long-term forecasting needs, providing flexibility for various applications within commodity trading.

The model is customizable and scalable, designed to adapt to new data and configurations. This includes the ability to incorporate custom events and other influential factors, ensuring continued relevance and accuracy as new information becomes available. By effectively handling outliers and minimizing loss functions, this hybrid E-MKLSTM and Neural Prophet model outperforms existing approaches such as LSTM with Moving Averages, Gaussian Process based LSTM, Facebook Prophet called the fbProphet. Consequently, this model stands out as an optimized, reliable method suitable for complex, multi-faceted business domains, offering enhanced accuracy, robustness, and interpretability in commodity price forecasting.

8. ORGANIZATION OF THE THESIS

Chapter 1 gives an introduction about commodity trade market and its classification, techniques used in commodity market forecasting, motivation and research objectives.

Chapter 2 discusses and analyses the findings in the domain of commodity market using various methodologies based on literature review.

Chapter 3 explains the first contribution to this research work in building a price forecasting model using Enhanced Multi-Kernel Long Short Term Memory (LSTM) with Dropout Regularization evading outliers bringing efficiency through weight adaptations.

Chapter 4 describes the second contribution to the research work in building an enhanced price forecasting model using integrated Neural Prophet with Anomaly Detection for optimizing signal strength and forecast for longer horizon periods.

Chapter 5 elucidates the third contribution using a Hybrid approach using Enhanced Deep Learning Neural Network with LSTM and Neural Prophet with Regressors for achieving optimization and enriches decision making for managing transactions efficiently in commodity trading.

Chapter 6 analyses and compares performance analysis of the proposed methods based on error detection metrics.

Chapter 7 elaborates on anomalies and transaction management strategies.

Chapter 8 concludes the research work and provides the possibility of future work for further development.

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